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REMARKS

I. Claim Rejections 35 U.S.C. § 102 or 35 U.S.C. § 103(a)

In the Office Action dated January 23, 2007, the Examiner rejected claims 21-41 under 35 U.S.C 102(b) as being anticipated by Widrow (U.S. Patent No. 3,222,654).

The Examiner argued that Widrow teaches a logic circuit and an electrolytic memory element (arguing that is a "perceptron"), and these components are illustrated in FIGS. 1 and 2 of Widrow and described in the text of Widrow. In support of this argument, the Examiner referred specifically to Widrow, C1:10-14; C2:40-48; and C3:18-28. The Examiner stated that other related text of Widrow are identified in prior office actions.

The Applicant respectfully disagrees with this assessment. Widrow does not provide for any teaching and/or disclosure of a physical neural network. FIG. 1 of Widrow is a circuit diagram of an adaptive logic circuit that includes five input terminals 1, 2, 3, 4, 5 connected to variable gain devices a1, a2, a3, a4, and a5. The output of the gain devices is connected to a summer 11. A variable gain device is connected to apply a signal to the summer to establish the threshold level. C3:18-75 and C4:1-32 of Widrow generally describe the workings of this adaptive logic circuit. The logic circuit of FIG. 1 of Widrow, however, is not a neural network circuit nor does it describe the function of a neural network or neural network components such as a synapse.

Neural Network Not Taught/Anticipated by Widrow

A neural network, also sometimes known as a parallel distributed processing network, is a solution that is loosely modeled after cortical structures of the brain. It includes interconnected processing elements called nodes or neurons that work together to produce an output function. The output of a neural network relies on

PAGE 14/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

the cooperation of the individual neurons within the network to operate. Processing of information by neural networks is characteristically done in parallel rather than in series (or sequentially).

Generally, a neural network is an information-processing network, which is inspired by the manner in which a human brain performs a particular task or function of interest. Computational or artificial neural networks are inspired by biological neural systems. The elementary building blocks of biological neural systems are the neuron, the modifiable connections between the neurons, and the topology of the network.

Neural networks learn and remember in ways that resemble human processes. Artificial neural networks are systems composed of many nonlinear computational elements operating in parallel and arranged in patterns reminiscent of biological neural nets. The computational elements, or nodes, are connected via variable weights that are typically adapted during use to improve performance. Thus, in solving a problem, neural net models can explore many competing hypothesis simultaneously using massively parallel nets composed of many computational elements connected by links with variable weights.

In a neural network, "neuron-like" nodes can output a signal based on the sum of their inputs, the output being the result of an activation function. In a neural network, there exists a plurality of connections, which are electrically coupled among a plurality of neurons. The connections serve as communication bridges among of a plurality of neurons coupled thereto. A network of such neuron-like nodes has the ability to process information in a variety of useful ways. By adjusting the connection values between neurons in a network, one can match certain inputs with desired outputs.

A neural network is one of the claimed features of Applicant's invention. The logic circuit described at C3:18-75 and C4:1-32 of Widrow is <u>not</u> a neural network, because it does not contain the aforementioned features of a neural network nor

PAGE 15/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

Best Available Copy

result in neural network processing of information. Additionally, there is no teaching in Widrow of the parallel and simultaneously processing capability of a neural network. The Widrow device, despite being an "adaptive" device does not include nonlinear computational elements operating in parallel and arranged in patterns reminiscent of biological neural networks. The Examiner has not identified the specific portions of Widrow that teach this type of neural network functionality. The Widrow device also does not teach or disclose computational elements, or nodes, which are connected via variable weights that are adapted during use to improve performance. There is no hint in Widrow of this capability.

There is also no teaching in Widrow of neural network models that explore many competing hypothesis simultaneously using massively parallel nets composed of many computational elements connected by links with variable weights. This is, of course, taught by Applicant's invention and Applicant's claims. The Widrow device also does not include "neuron-like" nodes that can output a signal based on the sum of their inputs, the output being the result of an activation function. The summer 11 of the adaptive logic circuit of Widrow, for example, while operating as a summation device, does not provide this capability of neuron nodes that can output a signal based on the sum of their inputs with the output being the result of an activation function. Thus, it is clear that the adaptive logic circuit of FIG. 1 of Widrow is <u>not</u> a neural network. Widrow does teach an early learning device of sorts but does not teach, disclose or suggest a neural network. C1:10-14 and C2:40-48 of Widrow, in particular, do not provide for such a teaching of a neural network. C1:10-14 of Widrow, for example, refers generally to logic circuits and memory elements and adaptive memory elements, but does not provide any teaching of a neural network.

Applicants invention is not simply, however a neural network. Neural network nanoconnections are utilized in Applicant's invention. However, Applicant's invention relates to an electromechanical-based liquid state machine utilizing nanotechnology that includes a connection network and neural network connections

PAGE 16/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

disposed and free to move about in a liquid dielectric solution. Such a liquid state machine is not provided by Widrow.

Perceptron Not Taught/Anticipated by Widrow

Regarding FIG. 2 of Widrow, it is clear that the electrolytic memory element is not a perceptron. The perceptrons of Applicant's invention adjust their synaptic weights so as to produce a desired output and function as a "read-out" neuron. The exact rule that the read-out neurons utilize may vary, but in general such read-out neurons form a simple linear mapping between the neural circuits of Applicant's invention and the liquid state machine and the read-out neuron output.

A perceptron is actually in and of itself a type of artificial neural network that at its most basic level can be seen as the simplest kind of feed forward neural network: a linear classifier. The perceptron is therefore a kind of classifier that maps its input x (a vector of type Real) to an output value $f(x)$ (a scalar of type Real) calculated as follows:

$$f(x) = \langle w, x \rangle + b$$

where w is a vector of real-valued weights and $\langle \cdot, \cdot \rangle$ is the dot product(which computes a weighted sum). b is the 'bias', a constant term that does not depend on any input value.

The sign of $f(x)$ is used to classify x as either a positive or a negative instance, in the case of a binary classification problem. The bias can be thought of as offsetting the activation function, or giving the output neuron a "base" level of activity. If b is negative, then the weighted combination of inputs produces a positive value greater than $-b$ in order to push the classifier neuron over the 0 threshold. Spatially, the bias alters the position (though not the orientation) of the decision boundary. Since the inputs are fed directly to the output unit via the weighted connections, the perceptron can be considered the simplest kind of feed-

PAGE 17/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

forward neural network. A basic description of the perceptron is available online from Wikepdia at the following URL:

http://en.wikipedia.org/wiki/Perceptron

The question is whether or not the above accepted description of a perceptron and its functionality is taught by Widrow's memory element. A review of Widrow makes it clear that such a perceptron is not taught or suggested by Widrow's memory element.

The Examiner argued that the Applicant has disclosed a physical neural network that achieves functionality by the process of applying an electric field across two electrodes that are immersed in a liquid dielectric solvent containing nanoconductors. The Examiner further asserted that it is through the process of applying the electric field that the nanoconductors align to form physical neural network nanoconnectors between pre-synaptic and post-synaptic electrodes. The Examiner argued that such is a product by process and a neural network developed by the process of applying the electric field.

The Examiner further indicated that the arguments filed on November 29, 2006 related to claims 21-41 have been fully considered but were not persuasive. The Examiner acknowledged Applicant's remarks contained on pages 10-27 of the response dated November 29, 2006. The Examiner argued that from the MPEP 2113, the controlling point of concern is: "Even thought product-by-process claims are limited by and defined by the process, determination of the patentability is based on the product itself." (Citing In Re Thorpe, 777 F.2d 695, 698, 227 USPQ 964, 966 (Fed. Cir. 1985).

The Examiner indicated that Applicant's invention discloses a physical neural network liquid state machine utilizing nanotechnology and argued that the prior art of Widrow anticipates a physical neural network liquid state machine. The Examiner cited FIGS. 1 and 2 of Widrow in support of this argument. From a product-by-process analysis, there is not a teaching of a product/device or any component by

PAGE 18/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

Best Available Copy

Widrow that functions as a liquid state machine. In other words, Widrow simply does not teach, disclose or suggest a liquid state machine as that term "Liquid State Machine" or LSM is known in the art. In fact, as will be explained shortly, the concept of an LSM did not even exist at the time of the Widrow reference. Additionally, one skilled in the art in the present day would not recognize Widrow as providing any teaching whatsoever of a liquid state machine.

Liquid State Machine Not Taught/Anticipated by Widrow

What exactly is a "liquid state machine"? An LSM (Liquid State Machine) is a particular and relatively recent type of device that was not even in existence at the time of the Widrow device. The conceptual framework of an LSM facilitates the analysis of the real-time computing capability of neural microcircuit models. It does not require a task-dependent construction of a neural circuit, and hence can be used to analyze computations on quite arbitrarily "found" or constructed neural microcircuit models. An LSM also does not require any a-priori decision regarding the "neural code" by which information is represented within the circuit. A good summary of what an LSM is can be found at the following web site:

http://en.wikipedia.org/wiki/Liquid_State_Machine

Of course, the LSM to date has been entirely a computational model. There has not been an actual physical hardware and nanotechnology based liquid state machine developed to date. Additionally, at the time of the Widrow reference (circa 1960's), the concept of an LSM had not even been developed. The computational algorithmic model of an LSM was not developed until long after the Widrow patent had expired, so it is improper to even suggest that Widrow provides for a teaching of an LSM, computational or otherwise.

The basic idea of an LSM as an LSM is known by those skilled in the art is that a neural (recurrent) microcircuit may serve as an unbiased analog (fading) memory (informally referred to as "liquid'" but of course not really a "liquid") about

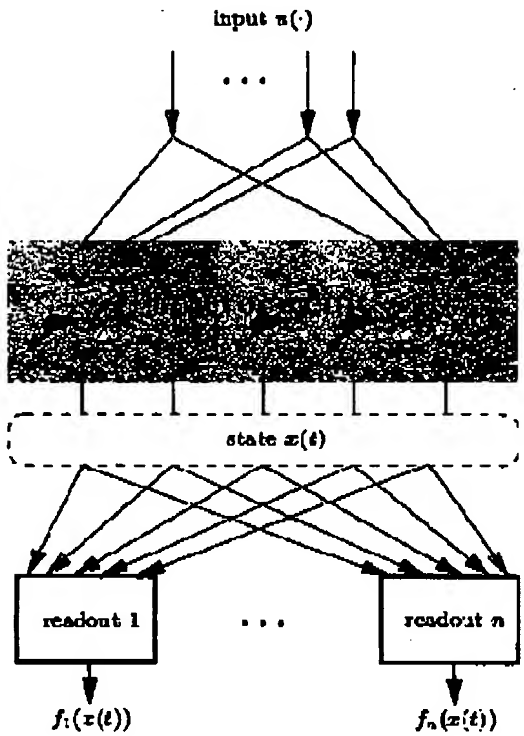
PAGE 19/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

Best Available Copy

current and preceding inputs to the circuit. The "liquid state" refers to analogy of a liquid but is not of course in and of itself a liquid. The word liquid in the name of the LSM comes from the analogy drawn to dropping a stone into a still body of water or other liquid. The falling stone will generate ripples in the liquid. The input (motion of the falling stone) has been converted into a spatio-temporal pattern of liquid displacement (ripples).

We refer to the vector of contributions of all the neurons in the microcircuit to the membrane potential at time t of a generic readout neuron as the liquid state x(t). Note that this is all the information about the state of a microcircuit to which a readout neuron has access. In contrast to the finite state of a finite state machine the liquid state of an LSM need not be engineered for a particular task. It is assumed to vary continuously over time and to be sufficient sensitive and high-dimensional that it contains all information that may be needed for specific tasks. The liquid state x(t) of a neural microcircuit can be transformed at any time t by a readout map f into some target output f(x(t)) (which is in general given with a specific representation or neural code). An illustrated example of a liquid state machine is provided in the figure below:

PAGE 20/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12



The Liquid State Machine (LSM). The recurrent microcircuit (liquid) transforms the input into states x(t), which are mapped by the memory-less readout functions f_1, ..., f_n to the outputs $f_1(x(t))$, ..., $f_n(x(t))$.

The liquid state machine is based on the concept that only the synapses of these readout neurons have to be adapted for a particular computational task. This requires that any two different input time series u(s), s ≤ t and v(s), s ≤ t which should produce different outputs at some subsequent time t put the recurrent circuit into two (significantly) different states $x_u(t)$ and $x_v(t)$ at time t. In other words: the current state x(t) of the microcircuit at time t has to hold all information about preceding inputs.

If the metaphorical "liquid" has this property it is possible to train a memory-less readout to produce the desired output at time t. If one lets t vary, one can use

the same principles to produce as output a desired time series or function of time t with the same readout unit. This yields the following (offline) procedure for training a readout to perform a given task based on the ideas sketched above.

1. Define the neural microcircuit to be analyzed
2. Record states x(t) of the microcircuit at various time points in response to numerous different (training) inputs u(×)
3. Apply a supervised learning algorithm to a set of training examples of the form [x(t),y(t)] to train a readout function f such that the actual outputs f(x(t)) are as close as possible to the target outputs y(t).

One advantage of this approach is that it is not necessary to take any temporal aspects into account for the learning task, since all temporal processing is done implicitly in the recurrent circuit. Furthermore no a-priori decision is required regarding the neural code by which information about preceding inputs is encoded in the current liquid state of the circuit. Note also that one can easily implement several computations in parallel using the same recurrent circuit. One just has to train for each target output a separate readout neuron, which may all use the same recurrent circuit.

The foregoing description of a "liquid sate machine" is simply not taught or disclosed or anticipated by Widrow. Widrow simply lacks any hint, suggestion or teaching of a "liquid state machine" by Widrow. The Applicant's specification, on the other hand, at paragraph [0028] indicates the following:

> Another type of neural network, which has been proposed, is known as a liquid state machine (LMS). A non-limiting and non-essential example of an LMS is disclosed in "Computational Models for Generic Cortical Microcircuits" by Wolfgang Maass, et al., Institute for Theoretical Computer Science, Technische Universitaet Graz, Graz, Austria, June 10, 1003. Note that the aforementioned Maass et al reference is referred to herein for general edification and background purposes only. It is believed that liquid state machines have not been implemented in the context of physical neural networks configured based on nanotechnology. A need thus exists for such devices, including methods and systems thereof.

PAGE 22/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

The Applicant refers to this section of Applicant's specification in order to make two points. First, a liquid state machine is a very particular type of neural network. Second, this type of neural network has only been implemented to date in the context of software simulations such as that disclosed in the Wolfgang Maass reference mentioned above, and not in an actual physical neural network, that is, of course, until the conception of Applicant's invention. Applicant goes on to describe the workings of Applicant's liquid state machine in paragraphs [00328] and [00329] of Applicant's specification as follows:

> FIG. 39 illustrates a system 3900 of interconnected neural circuitry referred to in the art as a Liquid State Machine, which can be adapted for use in accordance with an alternative embodiment of the present invention. Physical neural network 3900 thus comprises a Knowm™ enabled liquid state machine. System 3900 generally describes a neural network learning mechanism which can be applied to a physical neural network formed utilizing nanotechnology, as described herein. Such a network generally consists of two or more distinct neural modules. Inputs are presented to the first module, referred to as a Liquid State Machine or LSM. The LSM is generally a randomly connected network of neural circuits. Although the connections may be random, this is not always the case. Generally, the exact nature of the connections are not as important as the statistics of the connection, such as the amount of interconnectivity. However such a LSM is connected, its sole purpose is to provide what is referred to in the art as an "analog fading memory". In a liquid state machine, memory tends to fade, similar to the fading of ripples associated with liquid, such as water, as a result of input (e.g., a rock thrown in a pond) to the liquid or water at various times and locations thereof.
>
> The LSM can store, via patterns of neural activations, its recent past history. Other types of neural circuits can be utilized to extract the "state" of the LSM. A state-extracting neural circuit can be accomplished by a very simple learning neuron, such as, for example, a perceptron. Such perceptrons can adjust their synaptic weights so as to produce a desired output. Such perceptrons can be referred to as a "read-out" neuron. The exact rule that the read-out neurons utilize may vary, but in general such read-out neurons can form a simple linear mapping between the neural circuits within the LSM and the read-out neuron output.

Based on the foregoing and a thorough reading of Applicant's specification it can be appreciated that a liquid state machine or LSM of Applicant's invention, in order to function, includes the use of read-out neurons, a linear mapping between neural circuits and perceptrons that can adjust their synaptic weights to as to produce a desired output. Additionally, in an LSM memory tends to fade, similar to

PAGE 23/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

the fading of ripples associated with liquid, such as water, as a result of input (e.g., a rock thrown in a pond) to the liquid or water at various times and locations thereof. This does not mean of course that "water" is an element of a liquid state machine. The reference to "liquid" in the name "liquid state machine" is only a metaphor for how the device functions. That is, the word liquid in the name comes from the analogy drawn to dropping a stone into a still body of water or other liquid. The falling stone will generate ripples in the liquid. The input (motion of the falling stone) has been converted into a spatio-temporal pattern of liquid displacement (ripples).

Applicant believes that the attempt by the Examiner to compare the liquid dielectric of the Applicant's invention to the "liquid" of the liquid-state machine is a result of a lack of understanding of what a "liquid state machine" is. An LSM can be thought of as a decaying dynamic memory. In this way, it is not waves of a liquid that are decaying. It is neural signals in feedback loops within a neural network. In the system described by Applicant's invention, the dynamic decaying memory are the electrical signals being passed between neural circuits through the Applicant's synaptic device element. Widrow, on the other hand, does not teach or disclose this, but describes only a simple logic circuit and electrolytic memory element, which bares no similarity to the synaptic device element described by the Applicant.

A liquid state machine in the past has been presented by various researchers and software scientists as a computational construct and includes a large collection of units (called *nodes*, or *neurons*). Each node receives time varying input from external sources (the inputs) as well as other nodes. Nodes are randomly connected to each other. The recurrent nature of the connections turns the time varying input into a spatio-temporal pattern of activations in the network nodes. The spatio-temporal patterns of activation are read out by linear discriminant units. The soup of recurrently connected nodes will end up computing a large variety of nonlinear functions on the input. It is important to keep in mind, however, that such

PAGE 24/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

components and functions of a liquid state machine have only been presented in the context of neural network software simulations. Applicant believes that prior to Applicant's invention there has not been any prior art, which teaches, suggests or discloses an actual physical neural network (not software) that is an LSM.

Given this description of a liquid state machine, which is taught by Applicant's invention, it is difficult to identify the workings of a liquid state machine in the Widrow reference. It is also difficult to see how Widrow teaches, discloses or even suggests an LSM.

In a previous office action, the Examiner cited Widrow, C4:34-55 and argued that this citation shows an LSM. A review of C4:34-44 indicates that this citation provides no teaching, suggestion, or disclosure of an LSM. Instead, C4:34-44 simply refers to an electroplating device/process. Electroplating has nothing to do with an LSM. Again, keep in mind that the word "liquid" in LSM is simply a metaphor for the functioning of an LSM and has <u>nothing</u> to do with the fact that the dielectric may or may not be implemented in the context of a liquid dielectric solution. Widrow thus does not teach an LSM. The Applicant has provided sufficient information which indicates what an LSM is and is not. It is clear that Widrow does <u>not</u> teach, disclose or even suggest an LSM. Widrow is simply not an LSM as an LSM is known and taught in the neural network arts. The prior art of Widrow does not anticipate the LSM of Applicant's invention.

Definition of Nanotechnology

The Examiner further asserted that the Applicant has not provided an explicit definition of nanotechnology and consistent with ¶ 12. arguing that the molecular technology of Widrow applies (the Examiner argued "electrolyte" and cited FIG. 2). The Examiner argued that the Applicant associates "molecular technology" with embodiments of the disclosed invention at ¶ 100 of the specification.

PAGE 25/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

The Applicant respectfully disagrees with this assessment. The Applicant has in fact provided an explicit definition of technology. It is not necessary for the Applicant to provide a definition of "molecular technology" because the claims as amended refer to "nanotechnology". Applicant's specification provides a definition of nanotechnology, which is consistent with Applicant's claimed invention. For example, see Applicant's background section, which provides the following description of what constitutes nanotechnology:

> The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.
>
> In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. It is, however, becoming increasingly difficult to increase the number of elements on a chip utilizing existing technologies. At the present rate, in the next few years the theoretical limit of silicon-based chips will have been attained. Because the number of elements and components that can be manufactured on a chip determines the data storage and processing capabilities of microchips, new technologies are required for the development of higher performance chips.
>
> Present chip technology is also limited in cases where wires must be crossed on a chip. For the most part, the design of a computer chip is limited to two dimensions. Each time a circuit is forced to cross another circuit, another layer must be added to the chip. This increases the cost and decreases the speed of the resulting chip. A number of alternatives to standard silicon based complementary metal oxide semiconductor ("CMOS") devices have been proposed. The common goal is to produce logic devices on a nanometer scale. Such dimensions are more commonly associated with molecules than integrated circuits.
>
> The issue of interconnects in neural network hardware poses a serious problem. Because of the massive interconnectivity, a neural network constructed with standard integrated electronic methods can never reach the desired neuron and synapse density, simply because the interconnections overwhelm the largely 2-diminsional chip. It can thus be appreciated that almost any sort of 3-diminsional connectivity, no matter how simple, could offer tremendous benefits.
>
> Integrated circuits and electrical components thereof, which can be produced at a molecular and nanometer scale, include devices such as carbon nanotubes and nanowires, which essentially are nanoscale conductors ("nanoconductors"). Nanoconductors are tiny

PAGE 26/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

Best Available Copy

conductive tubes (i.e., hollow) or wires (i.e., solid) with a very small size scale (e.g., 0.7 to 300 nanometers in diameter and up to 1mm in length). Their structure and fabrication have been widely reported and are well known in the art. Carbon nanotubes, for example, exhibit a unique atomic arrangement, and possess useful physical properties such as one-dimensional electrical behavior, quantum conductance, and ballistic electron transport.

Carbon nanotubes are among the smallest dimensioned nanotube materials with a generally high aspect ratio and small diameter. High-quality single-walled carbon nanotubes can be grown as randomly oriented, needle-like or spaghetti-like tangled tubules. They can be grown by a number of fabrication methods, including chemical vapor deposition (CVD), laser ablation or electric arc growth.

Based on this description of what constitutes nanotechnology, it is clear that the Widrow device is <u>not</u> a nanotechnology-based device. The aforementioned language generally describes what is meant by "nanotechnology" and describes the context of Applicant's invention. Of course, it is understood by those who work with the nanotechnology arts that variations to the aforementioned description and examples are like to arise, but this description can be utilized as a general guideline for the context of "nanotechnology" in which Applicant's invention is provided.

Thus, the nanoconductors of Applicant's invention represent nanoscale conductors such as nanotubes, nanowires, nanoparticles and even DNA. For example, Applicant's paragraph 0091 indicates the following:

> Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules. A nanoconductor can also be implemented as, for example, DNA.

A nanoconductor as taught by Applicant's invention is thus a multi-atom structure such as a nanotube, a nanowire, DNA, etc., and not atoms and ions. Atoms and ions, for example, are simply just that...i.e., atoms and ions. The Applicant's use of nanotechnology-based devices and components relates to multi-atom structures that are built (man-made or natural) or synthesized. DNA, for example, is a naturally constructed multi-atom structure. Free floating ions and atoms utilized for example in the context of common P-well and N-well configurations are not such structures. Atoms and atomic ions do not represent nanoparticles/nanoconductors because "nanotechnology" seeks to use atoms as the

PAGE 27/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

building blocks of multi-atom structures. In this definition of nanotechnology, "ions" as taught by Widrow are not nanoconductors as taught by Applicant's invention or as "nanoconductors" are even known in the nanotechnological arts. The ions of Widrow are simply just that – ions. Nanoconductors as taught by Applicant's invention are electrically conducting components at the nanometer scale level such as carbon nanotubes, nanowires, DNA, and the like – but NOT "ions" as suggested in Widrow.

Also, it is important to keep in context the historical development of nanotechnology with respect to the date of the Widrow reference, which is dated in the 1960's. Thee was a first mention of some of the distinguishing concepts in nanotechnology (but predating use of that name) was in "There's Plenty of Room at the Bottom," a talk given by physicist Richard Feynman at an American Physical Society meeting at Caltech on December 29, 1959. Feynman described a process by which the ability to manipulate individual atoms and molecules might be developed, using one set of precise tools to build and operate another proportionally smaller set, so on down to the needed scale. In the course of this, he noted, scaling issues would arise from the changing magnitude of various physical phenomena: gravity would become less important, surface tension and Van der Waals attraction would become more important, etc. This basic idea appears feasible, and exponential assembly enhances it with parallelism to produce a useful quantity of end products. Such a discussion, of course, was not present in the Widrow reference.

The term "nanotechnology" was defined by Tokyo Science University Professor Norio Taniguchi in a 1974 paper (N. Taniguchi, "On the Basic Concept of 'Nano-Technology'," Proc. Intl. Conf. Prod. Eng. Tokyo, Part II, Japan Society of Precision Engineering, 1974.) as follows: "'Nano-technology' mainly consists of the processing of, separation, consolidation, and deformation of materials by one atom or one molecule." This was about a decade after the Widrow reference.

PAGE 28/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

In the 1980s, about twenty years after the Widrow reference, the basic idea of this definition was explored in much more depth by Dr. K. Eric Drexler, who promoted the technological significance of nano-scale phenomena and devices through speeches and the books Engines of Creation: The Coming Era of Nanotechnology and *Nanosystems: Molecular Machinery, Manufacturing, and Computation,* (ISBN 0-471-57518-6), and so the term acquired its current sense.

Nanotechnology and nanoscience got started in the early 1980s with two major developments; the birth of cluster science and the invention of the scanning tunneling microscope (STM). This development led to the discovery of fullerenes in 1986 and carbon nanotubes a few years later. In another development, the synthesis and properties of semiconductor nano-crystals was studied. This led to a fast increasing number of metal oxide nanoparticles of quantum dots.

A general discussion of nanotechnology and its historical roots and present development can be found at the following web site:

http://en.wikipedia.org/wiki/Nanotechnology

Nanotechnology implies the use of devices or components that are nanometer-scale in dimensions. The "ions" of Widrow are certainly not "nanoconductors" as taught by Applicant's invention. There is no indication of any nanometer-scale device dimensions in Widrow. The memory element of FIG. 2 of Widrow, for example, is clearly not a device that is nanometer-scale in dimensions. Additionally, Widrow provides no teaching of nanoconductors (e.g., nanotubes, nanowires, DNA, etc.) as taught by Applicant's invention. It is not clear, based on Widrow, how Widrow could possibly be modified one skilled in the art to function as a nanometer-scale based device, given its much larger dimensions.

The Examiner additionally argued that it is "the claims and only the claims that form the metes and bounds of the invention" and argued that limitations as cited in the independent claims 21, 38 and 40 clearly identify the product as a liquid state machine formed and associated with a neural network of molecular

PAGE 29/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

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connections. The Examiner stated that Applicant's discussion related to the characteristics of the "liquid" are merely part of the process to achieve a neural network and are not relevant under a product-by-process review.

The Applicant respectfully disagrees with this assessment and submits that given the amendments to the claims herein, a product-by-process review is no longer applicable. Applicant's claims as amended refer to actual product/device claims and separate process or method claims, but not to product-by-process claims. The Applicant submits that based on the foregoing amendments, any discussion of product-by-process claim analysis is rendered moot. However, assuming a product-by-process analysis does apply (which Applicant submits it does not), the resulting product (i.e., an electromechanical liquid state machine based on nanotechnology) is simply not taught, suggested or disclosed by Widrow. This is very clear given the aforementioned description of what actually constitutes a liquid state machine and the fact that the concept of an LSM was not even in existence at the time of the Widrow patent.

The Examiner further argued that at ¶ 106 of the specification, the Applicant applies an AC field across the terminals and that under such conditions, current will flow in the circuit with the dielectric. The Examiner argued that the only time a current will not flow in a circuit with a perfect dielectric is when the application of a DC field has reached steady state. Applicant notes that the issue of a DC field is moot, given the fact that Widrow does not teach a dielectric and that a modification of the electrolyte of Widrow into some sort of dielectric would render the Widrow device useless. Without an electrolyte, Widrow will not function, so why would one skilled in the art even be tempted to modify Widrow to function with a dielectric? The electrochemical nature of Widrow would simply fail when used as a dielectric. The electrolytic memory of Widrow would not function if the electrolyte of Widrow, for example, is replaced with a dielectric material.

PAGE 30/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

Concerning an electrolyte, the Examiner argued that if a high portion of the solute does not dissociate to form free ions, such weak electrolyte will exhibit dielectric properties. The Examiner also asserted that conversely, if the voltage across the dielectric exceeds the breakdown level, substantial current flow. The Applicant notes, however, that if a high portion of the solute of Widrow does not dissociate to form free ions, then the Widrow device will not function. Widrow, which is an electrochemical-based device, would fail, so any modification of the electrolyte of Widrow as suggested by the Examiner would result in the breakdown of the Widrow device, which in turn would tend to lead one skilled in the art away from the use of a dielectric.

Widrow is an <u>electrochemical</u>-based device. This is clear throughout the entire teachings of Widrow, which is based on <u>electrochemistry</u>. Widrow thus functions based on electrochemistry, which is the science of the reactions that take place at the interface of an electronic conductor (the electrode, which can be a metal or a semiconductor including graphite) and an ionic conductor (the electrolyte).

Applicant's invention, on the hand is <u>electromechanical</u> (i.e., electromechanical liquid state machine), meaning a device or process combining electrical and mechanical components. For example, the connection gap and the nanoconductors are a combination of electrical and mechanical components. The connection gap is a mechanical formation. The dielectric solution is utilized to induce a dipole in the nanoconductors. Thus, Applicant's invention offers electrical properties in association with the mechanics of the connection gap in combination with the dipole induced in the nanoconductors, but is clearly not based on electrochemistry.

Based on the foregoing, the Applicant submits that the rejection to claims 21-41 under 35 U.S.C 102(b) or 35 U.S.C. 103 as being anticipated by Widrow

PAGE 31/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

(U.S. Patent No. 3,222,654) has been traversed. The Applicant therefore respectfully requests withdrawal of the rejection to claims 21-41.

III. Conclusion

In view of the foregoing discussion, the Applicant has responded to each and every rejection of the Official Action. The Applicant has clarified the structural distinctions of the present invention via such amendments. Applicant respectfully requests the withdrawal of the rejections based on the preceding remarks. Reconsideration and allowance of Applicant's application is also respectfully solicited.

Should there be any outstanding matters that need to be resolved, the Examiner is respectfully requested to contact the undersigned representative to conduct an interview in an effort to expedite prosecution in connection with the present application.

Respectfully submitted,

Dated: April 16 2007

Kermit Lopez

Kermit Lopez
Attorney for Applicants
Registration No. 41,953
ORTIZ & LOPEZ, PLLC
P.O. Box 4484
Albuquerque, NM 87196-4484

PAGE 32/32 * RCVD AT 4/16/2007 4:38:35 PM [Eastern Daylight Time] * SVR:USPTO-EFXRF-1/14 * DNIS:2738300 * CSID:5053141307 * DURATION (mm-ss):09-12

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